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URBAN BUILT-UP FEATURE EXTRACTION AND ITS SPRAWL ANALYSIS IN CHENNAI METROPOLITAN AREA USING LANDSAT IMAGERIES

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ABSTRACT

Urbanization is a dynamic process that has shown considerable change in India with unprecedented growth rate over the last few decades. According to World Bank, India along with China, Indonesia, Nigeria and the United States will lead the Worlds Urban Population by 2050. The urban footprints are growing twice the rate of urban population as per the report on South Asia's urbanization. Current trend of urbanization has been tremendous that the use of space technologies will enable the urban planners, economists, environmentalists and ecologist and resource managers to come up with the sustainable methods for urban growth. The planners are currently devoid of information on the growth rate and the sprawl extent so that it will be helpful in providing the basic amenities like water, sanitation and electric it., etc. Remote sensing plays a vital role for such large scale and complex projects. Geo informatics is now extensively used to monitor the urban growth and their pattern of growth as it provides timely and synoptic view of the land cover. The urbanization process can be better understood using the images of different periods thereby providing the base for projecting the trends of urbanization. Such information can support policymaking in urban planning and natural resource conservation. The Land sat images provide ample information on urban change and thereby they help in mapping the city dynamics, its spatial dimension and developments. In this study, urban built up features are extracted from Land sat imageries using a new modified approach. The extracted urban features are then used to study the urban sprawl for Chennai Metropolitan Area.

KEYWORDS: Urbanization, Urban sprawl, Remote sensing, GIS, Built Up feature Extraction

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Original Article

INTRODUCTION

Urbanization is exceptionally dynamic in India with unprecedented urban growth rates occurred over the last few decades. By 2030, 40.76% of the country's population is expected to flock in the urban areas as stated in UN State of the World Population report in 2007. By 2050, China, Indonesia, Nigeria and the United States will face urban population surge by 2050 (Asian Development Bank, 2011)

In India the urban sprawl accounts for 55.3 percent of the country's total population but unfortunately the official census understates as 31 percent. According to the agglomeration index the population living in the urban areas accounts to 55.3 percent. The main reason being the increase in the population growth is maximum outside the fringes. Geo-informatics technology helps the city planners, environmentalists, ecologists and researchers in many disciplines to find a solution to problems that accompany urban growth.

Remote sensing plays a vital role for such large scale and complex projects. Remote sensing images are useful for monitoring the spatial distribution and growth of urban built-up areas because of their ability to provide timely and synoptic views of land cover (Guindon et al. 2004, Xu 2008, Bhatta 2009, Griffiths et al. 2010). Multi temporal analysis can be done with the help of remote sensing techniques which in turn help in processing future urbansation process. Such information can support policymaking in urban planning and natural resource conservation. Land sat images have been found to be very much useful for understanding the spatial dimensions and developments over the years for large cities. In this study, urban built up features are extracted from Land sat imageries using a new modified approach. The extracted urban features are then used to study the urban sprawl for Chennai Metropolitan Area.

AIM

The main aim of this study is to extract urban features from Land sat satellite images and use them to study urban sprawl in the study area.

OBJECTIVES

The main objectives of this study are as follows

- To formulate a built up index of urban features from coarse resolution satellite image
- To extract of urban features of study area (i.e. CMA) for 2005, 2010 and 2014
- To use extracted urban regions for estimating urban sprawl for the study area.

STUDY AREA

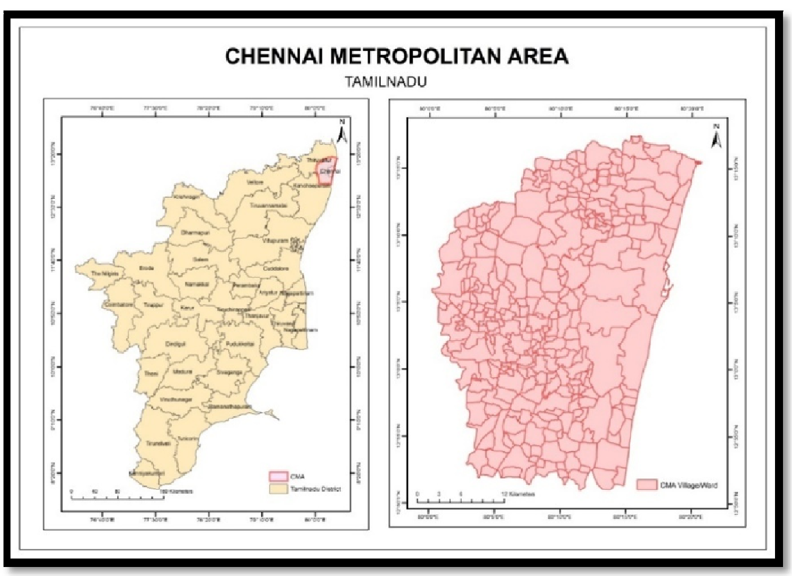

Figure 1: Study area, Chennai Metropolitan Area

The Chennai Metropolitan Area (CMA) comprises the city of Chennai (the capital city of the Indian state of Tamil Nadu), 16 Municipalities, 20 Town Panchayats and 214 Village Panchayats in 10 Panchayat Unions. It is located on the south–eastern coast of India in the north–eastern part of Tamil Nadu on the Eastern Coastal Plains. The study area extends to about 1189 sq.km. The Chennai district, part of Thiruvallur and Kancheepuram districts have been found to be a part of

Chennai Metropolitan area. 176 sq.km in Chennai district, 637 sq.km in Thiruvallur district (Ambattur, Thiruvallur, Ponneri and Poonamallee) and 376 sq.km from Kancheepuram district (Tambaram, Sriperumbudur and Chengalpattu taluks) form the Chennai Metropolitan Area. (Chennai Development Plan, 2006). The Chennai Metropolitan Area is proposed to be expanded further by including the entire districts of Tiruvallur and Kancheepuram and Arakonam. Chennai is sometimes referred to as the "Gateway to South India". The city is host to the third-largest expatriate population in India after Mumbai and Delhi. Chennai also known as Detroit of India has biggest industrial and commercial center in South India. Chennai was also named as the 9th-best cosmopolitan city in the world by Lonely Planet. The Chennai Metropolitan Area as recently as January 2015 has been ranked the fourth-largest economy in India, and the third-highest GDP per capita.

METHODOLOGY

Land sat cloudless imageries for the year 2005 (Land sat TM), 2010 (Land sat TM) and 2014 (Land sat OLI) i.e. a period of 14 years, was obtained from USGS server. The dates of Land sat imagery acquisition are 16th sept 2005, 16thoct 2010 and 9th sept 2014.The raw images were the preprocessed in Erdas Imagine 2014 software which was then stacked using composite band tool of Arc GIS 10.1 software. Spectral profile for various classes i.e. urban, water bodies, vegetation, barren land from stacked Land sat imageries were studied in Erdas Imagine 2014 to aid in creation of index for better urban extraction.

$$BI = \frac{SWIR2}{10*\sqrt{(SWIR1+TIRS1)}}$$

$$SAVI = \frac{(NIR-Red)(1+l)}{NIR+Red+l}$$

$$MNDWI = \frac{Green-SWIR1}{Green+SWIR1}$$

3 index images were derived from the Land sat images which are SAVI (0.5 value was taken for *l*), MNDWI and BI for vegetation, water bodies and urban region respectively using the above mentioned formulae.

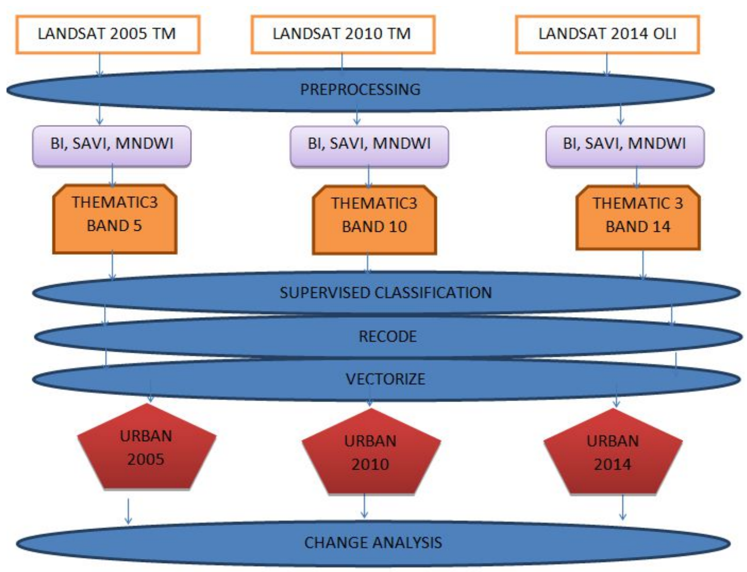

Figure 2: Methodology Flow Chart

These indices are then stacked and supervised maximum likelihood classification is performed. This is then followed by recoding to combine similar classes and thereby reducing the class dimensionality. The accuracy of classification and semi-automatic extraction is verified through visual interpretation using Google earth images.

The classified images then are converted into vector datasets which are then analyzed in Arc GIS 10.1 for change dynamics to estimate urban sprawl.

RESULTS & DISCUSSIONS

The proposed new built up index makes use of SWIR and TIR ranges of energies for extraction of built up regions. It has been observed that, this new built up index shows better differentiation between built up and barren land features similar to the Enhanced Built-Up and Bareness Index (EBBI) proposed by Abd. Rahman As-Syakur et al, 2012.

Instead of extracting urban features directly from the proposed index image, the methodology proposed by Hanqiu Xu, 2007 is used with a slight modification for better accuracy to urban features extracted. The proposed new built up index is used instead of NDBI index together with SAVI and MNDWI to create a 3 thematic-oriented band combination. Supervised maximum likelihood classification is employed as it gives best accuracy. Training sets i.e. signature datasets for the classification is created using visual interpretation and field knowledge.

It has been observed that the 3 thematic –oriented band combinations can be used to derive road network from moderate resolution image such as Land sat with proper signature.

The classified image is then recoded to reduce the class dimensionality to four. Since urban is the only region of interest only 4 major classes of land use which are Built-up, Water bodies, Vegetation and Barren-land are considered.

Increase in urban area is observed from 2010 to 2014 (from 434 km^2 to 557 km^2 approx.) whereas increase in urban area from 2005 to 2010 is comparatively negligible. Gradual decrease in vegetation is observed from 2005 to 2014 (from 503 km^2 to 465 km^2 approx.). Gradual decrease in barren is also observed from 2005 to 2014 (from 156 km^2 to 90 km^2 approx.). An unexpected anomaly in water regions has been observed with a significant increase of water area in the year 2010. This may be due to better capacity of Sriperumbudur, Ponneri and other small reservoirs also the wet/ water logged areas of Thiruvallur district in CMA. The change analysis (with what has changed to what by how much information) is represented in the tables 1, 2, 3 and figure 5.

It can be observed that the direction of sprawl in CMA is predominant southwards compared to others. This may be mainly because of IT companies along the OMR road, real estate along the ECR road and proximity to tourist spots, recreational centers, etc.

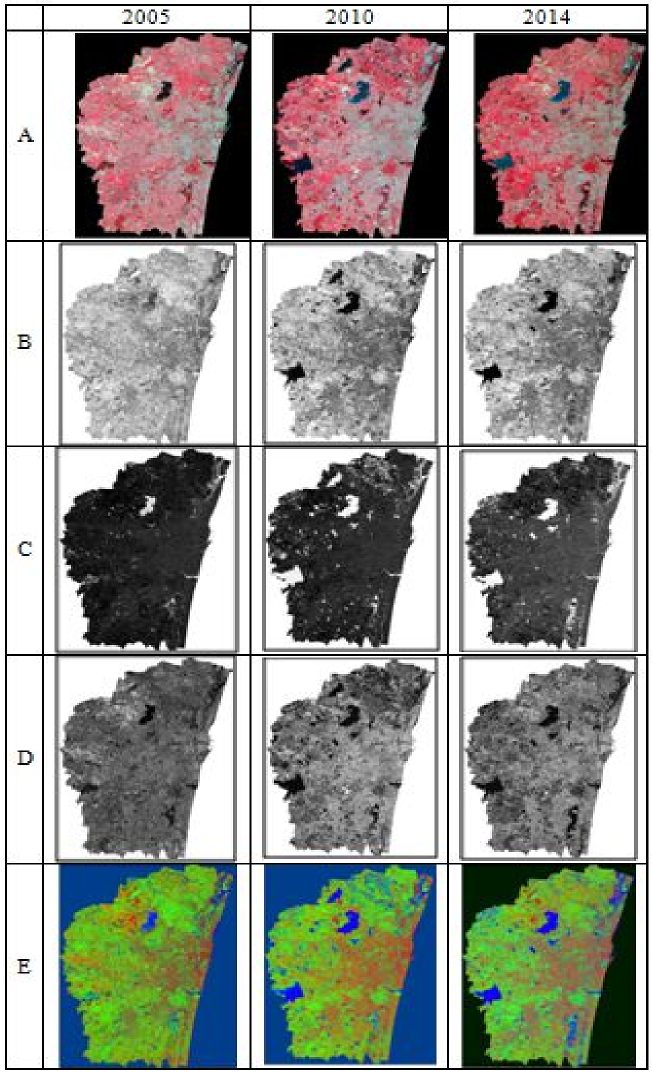

Figure 3: (From Top) Raw Land sat NIR, Red and Green Band Combinations (A), SAVI(B), MNDWI(C), BI(D) and Thematic Oriented band Composition(E)

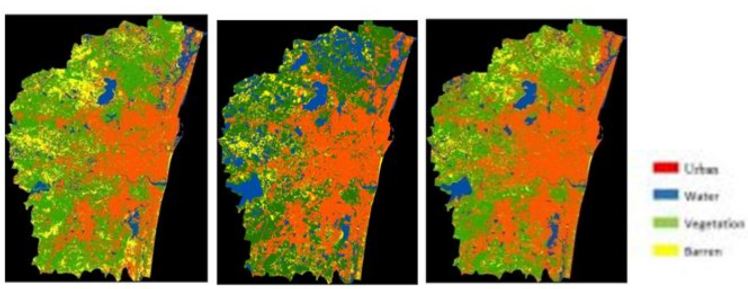

Figure 4: Classified Images (from Left to Right) 2005, 2010 and 2014

Table 1: Change Matrix 2005-2010

	2010				
2005	CLASS	URBAN	WATER	VEGETATION	BARREN
	URBAN	328.22	35.28	61.14	18.09
	WATER	13.31	56.21	15.67	2.25
	VEGETATION	63.08	50.79	349.16	41.56
	BARREN	29.75	24.08	55.94	45.54

Table 2: Change Matrix 2010-2014

	2014				
2010	CLASS	URBAN	WATER	VEGETATION	BARREN
	URBAN	389.55	3.33	25.51	15.99
	WATER	45.26	62.20	44.86	14.03
	VEGETATION	92.48	9.72	352.84	26.86
	BARREN	31.01	0.51	42.24	33.69

Table 3: Change Matrix 2005-2014

	2014				
2005	CLASS	URBAN	WATER	VEGETATION	BARREN
	URBAN	358.92	11.43	56.29	16.11
	WATER	29.06	41.18	12.93	4.25
	VEGETATION	127.31	14.65	332.89	29.71
	BARREN	42.99	8.48	63.33	40.52

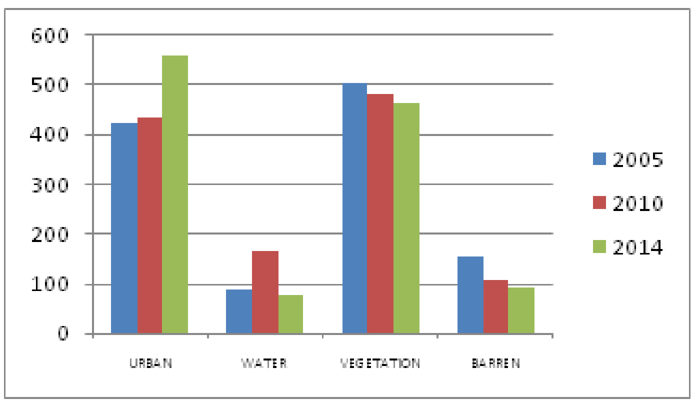

Figure 5: Temporal Variation of Urban, Water, Vegetation and Barren Land features (2005-14)

CONCLUSIONS

In this study, a new index that has capability of differentiating built up regions and bare land have been used together with indices for vegetation and water (SAVI and MNDWI) for extraction of urban features.

Use of thematic oriented band combination dramatically reduces data correlations and redundancy between multispectral bands, significantly avoiding the spectral confusion between the land-use classes, and thus largely improves the extraction accuracy.

The proposed method was effective at differentiating built-up and bare land areas in an urban area. It was also observed that the proposed method has capability of extracting major road/rail network from medium resolution satellite imagery sources for which further research is required.

There are a number of limitations in this work. This index can only map broad urban areas. But further classifying them into industrial, commercial and residential areas is not possible. Secondly, the proposed method is still unable to separate urban areas from barren with 100% accuracy, some areas of urban and barren area do misclassify. Finally the proposed method should e tested in other geographic areas. Extraction using the logic calculation method can also be employed instead of supervised classification. Extraction using the logic calculation method would be fast and objective, as it does not need to manually test a threshold value repeatedly.

The extracted urban features are then used to study urban sprawl for the last 15 years. A growth type of urban sprawl shows a transition of mono- to polycentric growth.

REFERENCES

1. *Asian Development Bank (2011), Asia 2050: Realising the Asian Century, Asian Development bank, Manila.*
2. *Abd. Rahman As-syakur, I Wayan Sandi Adnyana,I Wayan Arthana and IWayanNuarsa, Enhanced Built-Up and Bareness Index (EBBI) for Mapping Built-Up and Bare Land in an Urban Area, Remote Sens. 2012, 4, 2957-2970; doi:10.3390/rs4102957*
3. *B. Bhatta, S. Saraswati, D. Bandyopadhyay, Urban sprawl measurement from remote sensing data, Applied Geography 30 (2010) 731–740*
4. *H. Taubenböck, M. Wegmann, A. Roth, H. Mehl, S. Dech, Urbanization in India – Spatiotemporal analysis using remote sensing data, Computers, Environment and Urban Systems 33 (2009) 179–188*
5. *He, C.; Wei, A.; Shi, P.; Zhang, Q.; Zhao, Y. Detecting land-use/land-cover change in rural–urban fringe areas using extended change-vector analysis. Int. J. Appl. Earth Observ. Geoinf. 2011, 13, 572–585.*
6. *P. Thiruvengadam, Automatic Extraction of Surface Waterbodies and Change Detection, SRFP report 2013*
7. *Peter Ellis and Mark Roberts., (2016)., Leveraging Urbanization in South Asia., Managing Spatial Transformation for Prosperity and Liveability, International Bank for Reconstruction and Development / The World Bank.*
8. *S. MahalakshmiGowsalya, Automatic Extraction of Urban Features of Hydrabad& Surroundings from Landsat Multispectral Data AndUrbanisation Induced loss of Waterbodies, SRFP report 2013*
9. *Weng, Q. Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. Remote Sens. Envirn. 2012, 117, 34–49.*
10. *Xu, H. A new index for delineating built-up land features in satellite imagery. Int. J. Remote Sens. 2008, 29, 4269–4276.*
11. *Xu, H. Extraction of urban built-up land features from landsat imagery using a thematic-oriented index combination technique. Photogramm. Eng. Remote Sens. 2007, 73, 1381–1391.*
12. *Xu, H., 2005. A study on information extraction of water body with the Modified Normalized Difference Water Index (MNDWI), Journal of Remote Sensing, 9(5):511–517.*
13. *Zha, Y., J. Gao, and S. Ni, 2003. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery, International Journal of Remote Sensing, 24(3):583–594.*